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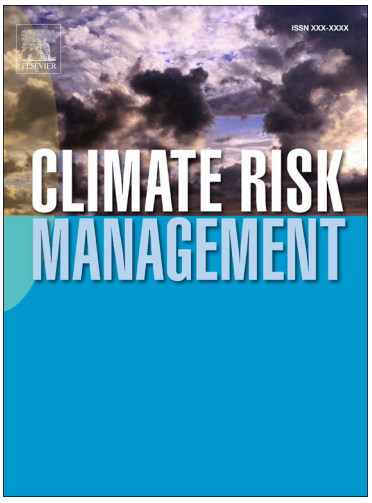

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A Stress Test for Climate Change Impacts on Water Security: a CRIDA Case Study

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Abstract

Since the impacts of climate change will be felt most directly through changes in water availability and water security, adequate tools are required to support water resources management decisions for the medium and long term. The Climate Risk Informed Decision Analysis (CRIDA) provides a pathway for more localized vulnerability assessments of water resources under climate change, while encompassing the uncertainty of current global climate projections. Within this framework, this paper demonstrates a climate stress test to identify changes in key performance indicators defined through local stakeholder consultations using a bottom-up approach. When applied to a case study in the Limari River basin in Chile, the stress test highlights the vulnerability of the reservoir system to climate variability and change, through a comprehensive analysis of 43 Global Circulation Models, of which 34 were retained. The Level of Concern (LoC) was defined as high, due to a high

plausibility for entering into adverse water security conditions, that are expected to provoke a significant impact in the highly productive areas of the watershed. As demonstrated by the case study, the climate stress test provides a relevant assessment tool for potential climate change impacts on critical components of the water system in vulnerable catchments.

Keywords: risk management; water security; climate change; CRIDA, Chile

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1. Introduction

Over the last decade, reports on the potential impact of climate change on water resources have shaped the debate, providing regional or country-based assessments of projected temperature and precipitation changes. Particularly the Intergovernmental Panel on Climate Change (IPCC) reports have provided an overview of current scientific knowledge on the information of Global Circulation Models (GCMs) and their projections under different emission scenarios (IPCC, 2014). This has resulted in a clear understanding that climate change is affecting the onset, duration and intensity of extreme hydro-meteorological events (Johnson and Weaver, 2009; Wood et al., 1997), as well as the climatological averages. Stationarity can therefore no longer be assumed (Milly et al., 2008), causing that historical records only provide insights in current or past climate and cannot be used to inform about future water challenges.

To inform on expected changes in the drivers of the hydrological cycle due to climate change, GCMs are our best available information (Kundzewicz et al., 2007). However, their coarse spatial and temporal resolution provides challenges on how to translate them to the river basin level (García et al., 2014; Kundzewicz and Stakhiv, 2010), where climate risk management strategies and adaptation policies need to be implemented. Therefore, several methods have been proposed to incorporate climate change impacts in the decision making process at the local level, that can be summarized as top-down or bottom-up approaches.

The top-down approach for evaluating future climate scenarios builds further on storylines of future economic, technological, and social development or 'representative concentration pathways' (RCP) scenarios (Moss et al., 2010), providing guidance for projections of both future water availability and future water consumption. Nevertheless, the top-down approach relies heavily on GCM output, which may well be an underestimate of the true expected climatic variability (Ray and Brown, 2015), as they focus on mean future conditions (Stainforth et al., 2007), lacking the ability to inform on climate extremes (Olsen and Gilroy, 2012), particularly precipitation variability (Rocheta et al., 2014), while amplifying the effects for runoff estimates (Fekete et al., 2004; Hawkins and Sutton, 2011), which are particularly important for water resources management.

The bottom-up approach starts by defining a particular water security challenge first. Based on the identified issue, a set of scenarios are generated that explore the vulnerability of the

hydrological system by adjusting the climate as well as other socioeconomic drivers of the system to evaluate its performance across a wide range of conditions (Ben-Haim, 2006; Brown et al., 2011; Prudhomme et al., 2010; Ray and Brown, 2015). This allows to realize a much more complete analysis of system performance than only focusing on IPCC scenarios under the top-down methodology. The scenarios explored in the bottom-up approach are used to identify suboptimal system performance, and to identify the combination of conditions that would lead to system failure. In particular, critical thresholds are identified that can be tested under current climate and future climate projections, as proposed by Kwadijk et al. (2010) and Brown and Wilby (2012). The approach therefore allows exploring the decision space, providing complete information on threats and challenges to ensure water security. An additional benefit of bottom-up methods is that the uncertainty associated to the climate change projections of the GCMs only enter the analysis at the stage when assessing plausibility of impact. Therefore, the problem of propagating uncertainty as described by Wilby and Dessai (2010) is significantly improved (Carter et al., 2007; Jones, 2000).

In the bottom-up approach, a climate stress test can be used to efficiently explore the performance of alternatives, by which an option is exposed to a variety of plausible climate and non-climate changes, to identify water security vulnerabilities. Weather generators are often used as the analytical engine to explore the climate aspects of the stress test (e.g. Ray and Brown, 2015), as they are a common tool for extending meteorological records (Wilks, 2002); disaggregating seasonal hydroclimatic forecasts (Verbist et al., 2010); and downscaling coarse, long-term climate projections to fine-resolution, daily weather for impact studies (Greene et al., 2012b; Kilsby et al., 2007; Wilks, 1992).

When combined with appropriate decision making tools, these weather generators can provide adequate and actionable information on system vulnerabilities for decision makers in river basins (Milly et al., 2008). Particularly by generating 'response surfaces' (Groves and Lempert, 2007), the scenarios for which the system shows the most vulnerability can be communicated more effectively to decision makers (Parker et al., 2013). They are also a means to represent uncertainty into the decision-making process, addressing a gap that is present in the top-down approach (Barsugli et al., 2009, 2012).

The use of multi-criteria approaches to water resources management can be traced back as far as the Harvard Water Program (Maass et al., 1962), but this programme adopted a stationarity approach, which has been invalidated (Milly et al., 2008). The Shared Vision Planning has further expanded that approach, and started integrating elements of non-stationarity through decision scaling (Ray and Brown, 2015) to optimize decision making for water resources management. Additional elements on adaptation planning under uncertainty have been further integrated to form the Climate Risk Informed Decision Analysis or CRIDA (Mendoza et al., 2018), co-published by UNESCO, providing a bottom-up participatory approach for climate risk management in the water sector. A first concrete CRIDA case study was presented by Gilroy and Jeuken (2018), demonstrating how CRIDA complements and extends the Integrated Water Resources Management (IWRM) planning process under uncertainty.

This paper provides further support for the practical implementation of the first two steps of CRIDA in river water basins, by presenting a generic climate stress test tool to efficiently explore a wide range of climate risks to water resources systems. In the methodology section, the CRIDA approach for climate stress testing is elaborated, and is followed by a real-world case study for the Limarí river basin in Chile, providing a step-by-step overview of the climate stress test methodology and results, as well as the level of concern regarding the climate change impacts for the basin. The paper ends with concluding remarks, highlighting some of the current limitations and a proposal for the way forward.

2. Materials and Methods

The materials and methods section is divided into two parts. The first part describes the characteristics of the case study that will be used to demonstrate the climate stress test methodology, that is presented in the second part of this section.

2.1. Characteristics of the case study area

2.1.1. Geographic characteristics

The Limarí river basin is located in Chile, in the Region of Coquimbo between the valley of the Elqui river northwards and the valley of Choapa in the south (Fig. 1). The Limarí province extends between 30°09’ and 31°22’ South Latitude, covering a surface of approximately 11,800 km^2. The Limarí River originates from the union of two rivers: Río Grande and Río Hurtado, both having their source in the Andes mountains (4500 m a.s.l.). The union is located

about 4 km above Ovalle city and the river reaches the sea after following a 60 km trajectory (Figure 1).

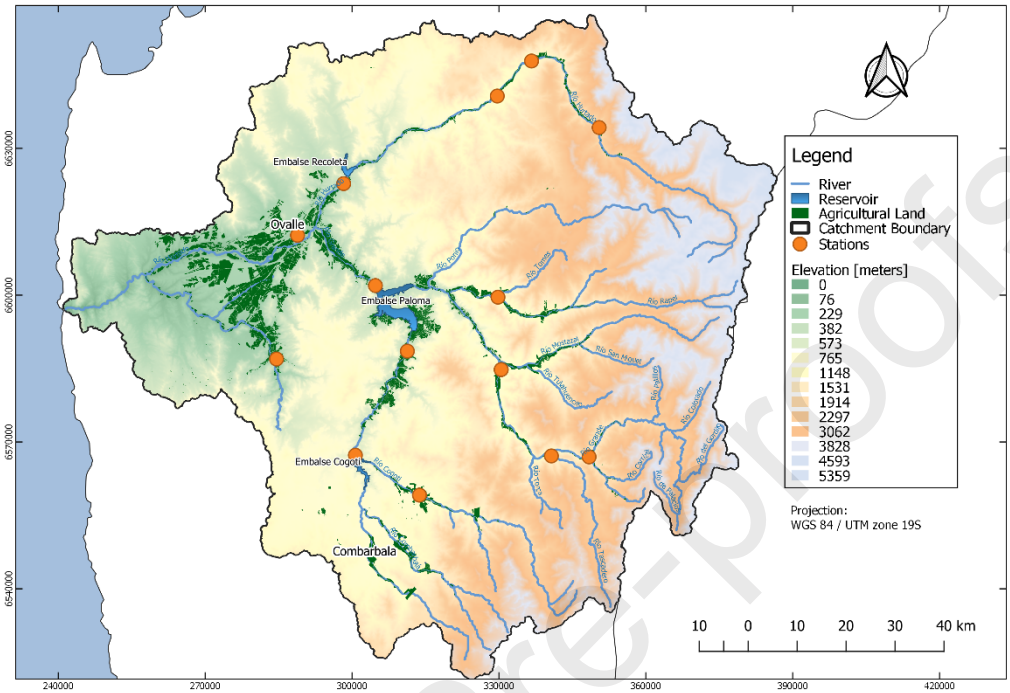

Figure 1 Map of the Limarí River Basin

The river basin hosts a wide range of economic activities in the catchment that depend strongly on water usage, mainly agriculture, mining industry and hydropower generation, creating competing water uses (Vicuña et al., 2014). The Limarí river basin is the most important agricultural area of the Norte Chico of Chile, since its water irrigates more than 70,000 ha. A great part of the valley consists of irrigated prairies, used for cattle raising, while horticultural activity is widespread. Orchards take up the largest part of the agricultural area of the basin (34%), especially citrus fruits, followed by annual crops (24%) and vineyards (21%).

The Limarí River Basin covers three different climates: the semiarid with abundant cloud formation, the temperate semiarid with winter rains and the cold semiarid with winter rains. Its hydrology is dominated by highly variable snowmelt and the precipitation amount exhibits strong spatial variation, ranging from about 100 mm at the coast to 300 mm at the top of the Andes. In general, this river basin has an average total annual amount of precipitation of 150 mm, of which 80% of total precipitation occurs in winter months. Most water resources of the Limarí River basin are stored in the Andes Mountains as snow and ice and become available

for irrigation use only during the spring and summer months (from October to March). Figure 2 illustrates the average temperature and precipitation of the Limarí River. Interannual variability is high, with a coefficient of variation of 0.7, which is strongly linked to 'El Niño Southern Oscillation' or ENSO (Souvignet et al., 2011; Verbist et al., 2010).

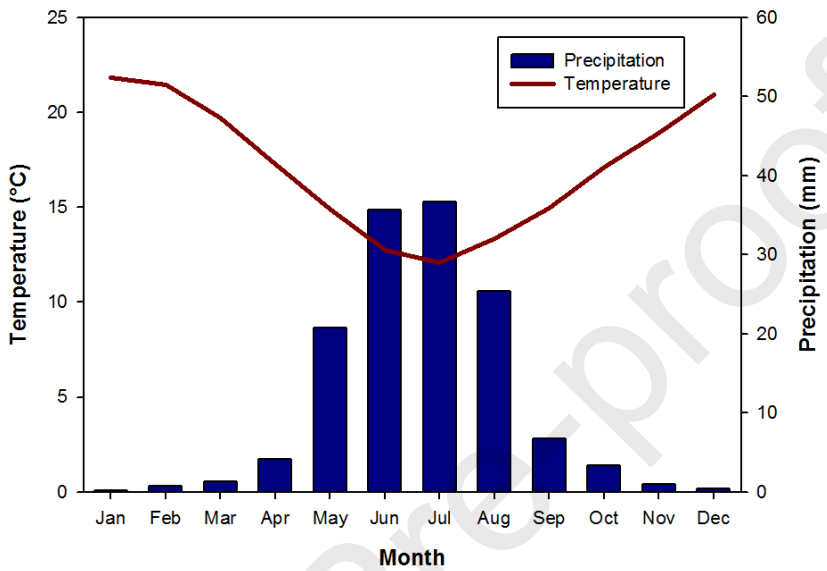

Figure 2 Monthly averages of Precipitation and Temperature at the Paloma reservoir

The high variability in water availability, combined with the ideal climatic conditions for the development of more intensified and export-oriented agriculture, motivated the construction of the Paloma Reservoir, which was finished in 1968. This reservoir was designed to store 740 hm^3, which is almost twice the annual average flow volume. A set of rules govern the operation of this reservoir, along with the other two in the basin (Recoleta Reservoir, 100 hm^3; Cogotí Reservoir, 150 hm^3, see Figure 1). Together, these dams form the sub-basin called the Paloma system.

In recent years however, an unusually long drought (2010-2015) has changed expectations with regard to climate variability in the region (Garreaud et al., 2017). This situation has led to dramatically low reservoir levels and continuous reductions in water supply.

In addition, due to the already high levels of irrigation efficiency and large amount of acreage devoted to permanent water demand crops, the effectiveness of the portfolio of options available to farmers to accommodate to these stressed conditions has been reduced. It also raises the question if the current water allocation is sustainable when considering the impact

of additional population growth and climate projections affected by climate change. Specifically, for the central-northern area of Chile, climate projections show a general trend of reducing precipitations in the IPCC scenarios (IPCC, 2014), in addition to the already observed increase in temperature, that is affecting the water consumption of crops and evaporation from the reservoir, as well as reducing the snow and ice reserves in the river basin.

2.1.2. Data sources

As indicated in Figure 1, fourteen stations with daily precipitation and temperature records were used in the climate stress test, that were provided by the General Water Directorate (DGA) and the Meteorological Directorate of Chile (DMC). The stations are located between a wide range of altitudes from 220 m until 1920 m a.s.l. All stations had a data series that covered the period 1969-2014, and the 30-year period 1981-2010 was selected as the historical reference period, in line with the recommendation from the WMO (2017).

2.2. Climate Risk Informed Decision Analysis (CRIDA)

The Climate Risk Informed Decision Analysis or CRIDA provides a planning tool for water resources management under (climate change) uncertainty, using a five-step approach. The full methodology is described by Mendoza et al. (2018) and is available from the UNESCO publications repository. In summary, the five steps are here presented.

Step 1: Decision Context: In this first step, the focus of the climate change adaptation development needs to be clearly defined. This involves an all-inclusive stakeholder engagement to define key variables that need to be considered in subsequent steps, as well as their critical thresholds beyond which negative impacts are expected.

Step 2: Bottom-up Vulnerability Assessment: Building on the critical indicators defined by the stakeholders in step 1, a detailed stress test is applied to identify climate change impacts and those of non-climatic drivers on the identified performance indicators.

Step 3: Formulate Robust and Flexible Adaptation Actions: In the third step, ‘adaptation pathways’ are identified that evaluate all potential options with respect to the results of the climate stress test in step 2, while including uncertainty explicitly in the process.

Step 4: Evaluate Alternative Adaptation Pathways: While the previous step generated a portfolio of potential options to address climate change impacts, in this step a financial and

institutional evaluation is developed to identify the best adaptation pathway under current conditions, combining both robust and flexible adaptation actions.

Step 5: Institutionalize Decisions: The last step of CRIDA ensures the integration of the decision framework into operational plans at the institutional level. This requires an effective mapping of governmental roles and mandates, as well as a review of financing options.

The first two steps will be further elaborated, as they are used and further developed in this paper.

2.2.1 Step 1: Identification of the Decision Context

In the first step of the CRIDA process, a stakeholder consultation meeting is required to identify the Decision Context, which involves the following aspects:

1. Define the water security vulnerability for the water basin

A first step in the stakeholder analysis includes the definition of a well-defined problem, which identifies the water security challenges, but should not include already predefined solutions. The list of water security challenges will further condition the stress test scenarios to be performed and the indicators to be considered. Therefore, it is crucial to involve the local stakeholders in the definition of these water security vulnerabilities.

2. Define sector-specific objectives and key performance indicators

A second step focusses on the definition of concrete objectives that need to be fulfilled to ensure water security in the river basin. The competing water uses, such as water supply for agriculture and drinking water, ecosystem benefits, hydropower production, profitable crops, among others, require the prioritization of clear objectives and constraints that guide the exploitation, design and operation of water resource systems in the river basin.

These objectives are in turn linked to performance metrics that facilitate an assessment of the river basin to deliver reliable, resilient and robust services and to achieve the stated goals and objectives.

Performance metrics quantify how climate change and other drivers impact the water security of the river basin. Therefore, the measures of performance should have direct relationships with external drivers such as climate, flow regime and demographic change.

In the case of water supply, the performance metrics should be dependent on climate variability and change. Possible options include the supplied water demand or overall water storage in the river basin needed to supply demand, but could also include targets of other productive sectors, environmental services and public water uses.

3. Define critical water security limits for the indicators identified

With respect to the identified performance metrics, thresholds need to be defined that should not be violated or that are considered of high negative impact if they would occur, in line with the proposed approach by Kwadijk et al. (2010) and Brown and Wilby (2012). These critical thresholds are used in the stress test to evaluate the risk of the river basin to enter into insecure water conditions as a result of possible future climate conditions. Therefore, the definition of critical thresholds is a fundamental element of the analysis to measure the reliability, resiliency, and robustness of water resources under the stress of climate change.

2.2.2 Step 2: Bottom-up Vulnerability Assessment

The Climate Stress Test

An important aspect of the vulnerability assessment is to develop a stress test to assess the water security condition under climate change impact. The approach adopted here uses the SIMGEN weather generator (Greene et al., 2012b) for those purposes, which has been successfully applied in in South Africa (Greene, 2012; Greene et al., 2012a, 2012b) and South America (Greene et al., 2015).

The approach uses decomposition by time scale (Greene et al., 2011) to separate the observed climatic variability into three components: century-scale climate trends, decadal variability and interannual variability. The methodology is fully described in Greene et al. (2012b, 2012a) and is summarized here in brief and presented in Figure 3.

The weather generator requires the input from daily precipitation and minimum and maximum temperature measurements from meteorological stations located in the area of interest. After checking these datasets for consistency, small gaps in the dataset are removed using the Multivariate Imputation by Chained Equations (MICE) (van Buuren and Groothuis-Oudshoorn, 2011).

In the first step, data are evaluated for available trends due to anthropogenic forcing, which is determined by comparing with the global mean temperature increase due to climate change. As the climate change component is modeled separately, this trend is removed from the station data. The remaining signal is considered natural variability and is split into two components to separate the deterministic subcomponents from the random aspects of interannual variability.

To detect the deterministic component in the data series, a wavelet analysis (Torrence and Compo, 1998) is used to evaluate for systematic, decadal variability, such as returning oscillations. For the second component, the remaining signal is considered a combination of random events that can be modelled using a vector autoregressive or VAR model (Greene et al., 2012b). The VAR model accounts for random (white noise) variations, but can also represent the short-term memory (red noise) that arises from ocean-weather interactions and which can generate "slow" fluctuations, including potentially long spells above or below the mean.

By fitting the appropriate VAR model to the observed data, a first output is the generation of a decadal time series representing the natural variability of precipitation and temperature for the river basin, consistent with the historical record. This will provide the background to which the other processes (daily variability and climate change trend) will be aggregated (Figure 3).

A separate pathway focuses on the climate change component, and consists of analyzing the 43 Global Circulation Models (GCMs) that form part of the Climate Model Intercomparison Project Phase 5 (CMIP5) (Taylor and Meehl, 2012). As a first step, monthly time series of precipitation and temperature are extracted for the river basin of interest, by intersecting the basin with the GCM grid and by averaging the GCM grid cells if more than one cell covers the basin. This involves both the historical period (1850-2005) and projected period (2006-2100).

Quality control is added in this step to detect those GCMs that are not representing well the natural variability of the observational record, and that are therefore expected to be less representative for projected changes as well (Anagnostopoulos et al., 2010; Kundzewicz and

Stakhiv, 2010). A correlation coefficient threshold of R^2=0.15 is used to detect those GCMs that perform weakly in representing observed conditions.

Using the selected GCMs, the percentage of change in precipitation for each increment of temperature is derived, creating a distribution of possible changes. This is an important step, as it indicates for the local river basin of interest what different changes in precipitation and temperature can be expected, based on GCMs that adequately represent the local conditions. This distribution also facilitates the sampling of different percentiles of the GCM projections, providing a pathway to select drier, median or wetter model precipitation projections for example.

The different subcomponents are then recomposed to generate a stochastic series of future projections with an annual-to-decadal timescale. In order to allow models to be run using higher time resolutions (monthly or daily) as well as to represent the spatial variability across the meteorological stations in the basin, the annual precipitation and temperature time series are downscaled using a K-nearest neighbor (KNN) approach to the daily time scale. Once a representative year of observed daily data is selected using KNN, the mean precipitation amount, minimum and maximum temperature are replaced with the projected value using a scaling approach. This ensures an adequate representation of local weather characteristics, including seasonal variations at the individual station level.

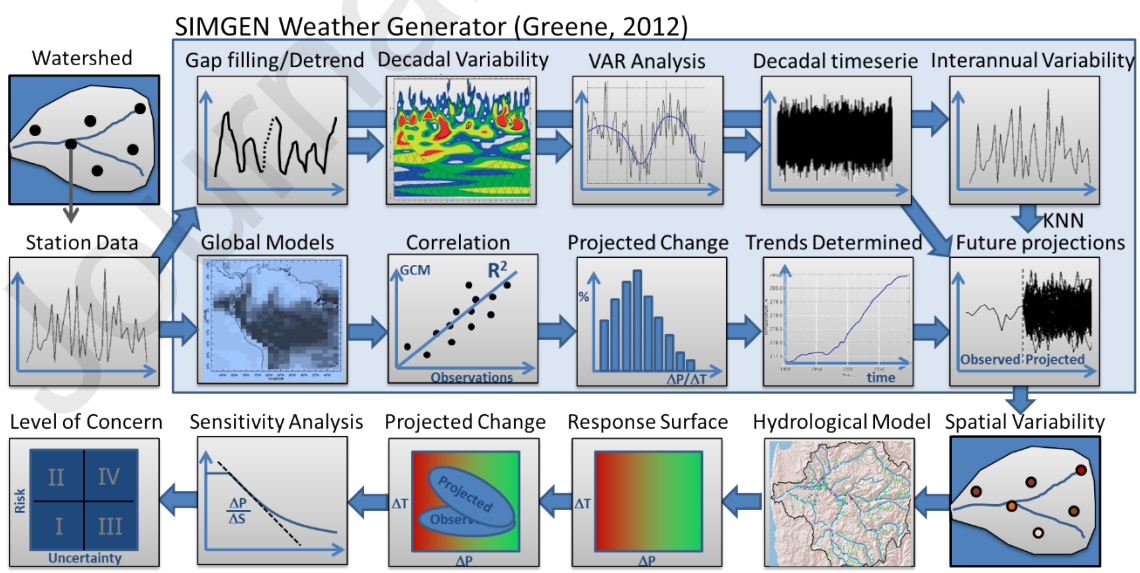

Figure 3 Schematic overview of the climate stress test

Using the SIMGEN weather generator, significantly different responses can be generated, as the full distribution of GCM projections can be sampled (possibly encompassing both wetting and drying scenarios), resulting in an unlimited number of possible time series. As such, the weather generator is well suited to explore the whole climate space that can be expected under climate change scenarios, evaluating the impact of global warming on all three variables (precipitation and minimum and maximum temperature), while maintaining their variable intercorrelation.

A last step in the climate stress test consists of routing the future climate projections through a water balance evaluation tool. This step can be generated with any hydrological model that provides insights into the process of water allocation to the final stakeholders and that allows to identify critical thresholds.

As the weather generator only provides insights into the expected changes in precipitation and temperature, the hydrological model can ingest these future projections and provide a plausible effect of these changes on the water security in the river basin. Different aspects of the hydrological system can be queried, such as drinking water in cities, unmet demand in agricultural areas, as well as groundwater and reservoir levels. This allows to identify those variables or 'performance indicators' that can be used in the subsequent step of climate stress testing.

A first analytical step involves sensitivity testing of the river basin model. The objective of this process is to define the response of the system to external drivers, such as temperature and precipitation. The range of conditions tested should be wide enough to encompass all observed and future climate states.

The second step of the process involves identifying the projected change of the river basin water availability and allocation with respect to the critical thresholds identified. This requires running the river basin model first in historical mode, identifying the range of normal conditions, including episodes of excess and deficit. Finally, the projected climate scenarios are run through the model, identifying how the range of model projections could alter water availability in the river basin, and generate chronic unacceptable performance below the critical thresholds for the basin.

The Level of Concern Analysis

The final step of the Vulnerability Assessment consists of a Level of Concern (LOC) analysis. This involves the evaluation of two different criteria: i) the risk of climate change and ii) the confidence in the stress test due to (analytical) uncertainty (Figure 5). To evaluate the risk of climate change, both the impact of climate change needs to be assessed, as well as the plausibility of this risk to occur.

Therefore, a sensitivity analysis is required to identify when a critical threshold of the river basin water security is likely to be overpassed, entering a vulnerable state. This allows evaluating both current climate, as well as future projections with respect to system performance, by identifying the elasticity of the system to climate change impact. System performance that is inherently less sensitive to change under plausible futures is at lower risk.

To evaluate the plausibility of climate change impacts within the time horizon of interest, an additional assessment is needed. Figure 4 provides conceptual examples of this type of assessment (Mendoza et al., 2018). In Figure 4a the sensitivity analysis suggests that the climate will become more stressful, and there is high sensitivity in performance towards unacceptable conditions, while the GCM models provide consistent forecasts. Under this situation there is high plausibility that the critical threshold will be surpassed in the planning horizon. In Figure 4b, all the climatic data components are the same, but the system is less sensitive in the domain of the evidence set, and it may be categorized as low plausibility for surpassing the threshold. Figure 4c is analogous to Figure 4a but the range of GCM forecasts are far broader. This figure could suggest that there is plausibility that the performance threshold will be surpassed, but because of the broad domain of the forecasted information it may also be categorized as having a higher level of analytical uncertainty.

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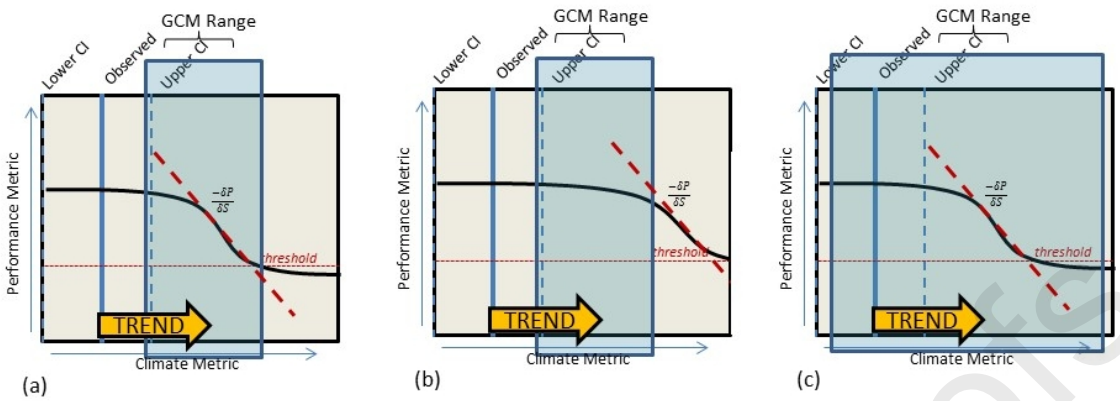

Figure 4 Examples of the climatic data and sensitivity components to assess plausibility of surpassing a critical threshold (modified from Mendoza et al., 2018)

This introduces the second criterion of the LOC analysis, the assessment of the (analytical) uncertainty of the stress test. Uncertainty comes from several sources in the analysis, including from the projected variables derived from GCMs, from the hydrological model uncertainty, specifically in data poor regions or regions with high spatial variability and complex topography, and from the measurement data used in the analysis. The level of uncertainty also informs about the type of adaptation strategies that should be prioritized in Step 3 of the CRIDA methodology: robust solution are preferred under low uncertainty, while high uncertainty would motivate the use of more flexible approaches. Combining the different criteria, a level of concern analysis indicates what the level of urgency should be to address the threat of climate change impact on the water resources allocation in the river basin, and what type of adaptation measures would be most appropriate (Figure 5).

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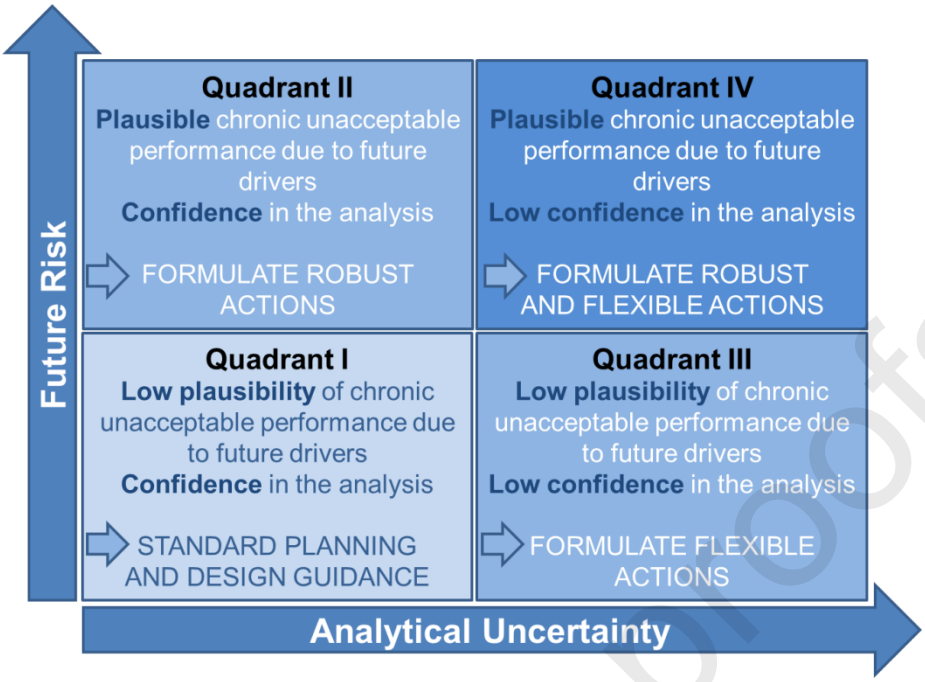

Figure 5 Level of Concern Matrix (modified from Mendoza et al., 2018)

3. Example application for the pilot river basin

3.1. Step 1: Identification of the Decision Context

As presented in the methodology section, there are several steps to develop the decision context to provide input to the climate stress test for the pilot river basin. Therefore, a stakeholder meeting was organized in 2016 with the water managers of the Limarí river basin, in order to define these three aspects, and the following inputs for the climate stress test could be further identified:

3.1.1. Definition of the water security vulnerability for the water basin

In recent years, an unusually long mega-drought from 2010 until 2015 (Garreaud et al., 2017) has changed expectations with regard to climate variability in the region. This situation has led to dramatically low reservoir levels and continued reductions in water supply (Figure 6). In addition, due to the already high levels of irrigation efficiency and large amount of acreage devoted to permanent water demand crops, the effectiveness of the portfolio of options available to farmers to accommodate to these stressed conditions has been reduced. As a result, large areas that were previously cultivated and covered with perennial crops (vinyeards, avocados and fruit trees) have been abandoned.

It also raises the question if the current water allocation is sustainable when considering the impact of additional population growth and climate projections affected by climate change. Specifically, for the central-northern area of Chile, climate projections show a general trend of reducing precipitations in the IPCC scenarios (IPCC, 2014), in addition to the already observed increase in temperature, that is affecting the water consumption of crops and evaporation from the reservoir.

The key drivers and stressors for change have therefore been identified to be the projected increase in temperature and reduction in precipitation as a result of climate change, as well as the increasing population growth, albeit to a lesser degree. Population growth is affecting mainly the increasing need for drinking water for the main city Ovalle. Instead of using it as a separate driver, population growth was integrated in the model by assuming a 2% population growth per year, in line with observed and expected trends.

Other drivers have also been considered, such as water use efficiency and the increase of cultivation area in the watershed. A large-scale study was developed to assess the impact of increased cultivation area and irrigation in the target area, demonstrating its unsustainability under current climate (CAZALAC, 2006; Orphanopoulos et al., 2013). Further agricultural expansion is therefore no longer pursued in the region, making a status quo or even a reduction in area a more likely scenario. In the same study, water use efficiency through the use of alternative cropping patterns and irrigation efficiency has been shown to only marginally improve water security in the watershed, and is also considered a potential solution instead of a driver. As such, it should be included in step 3 of the CRIDA methodology, where potential adaptation pathways are explored.

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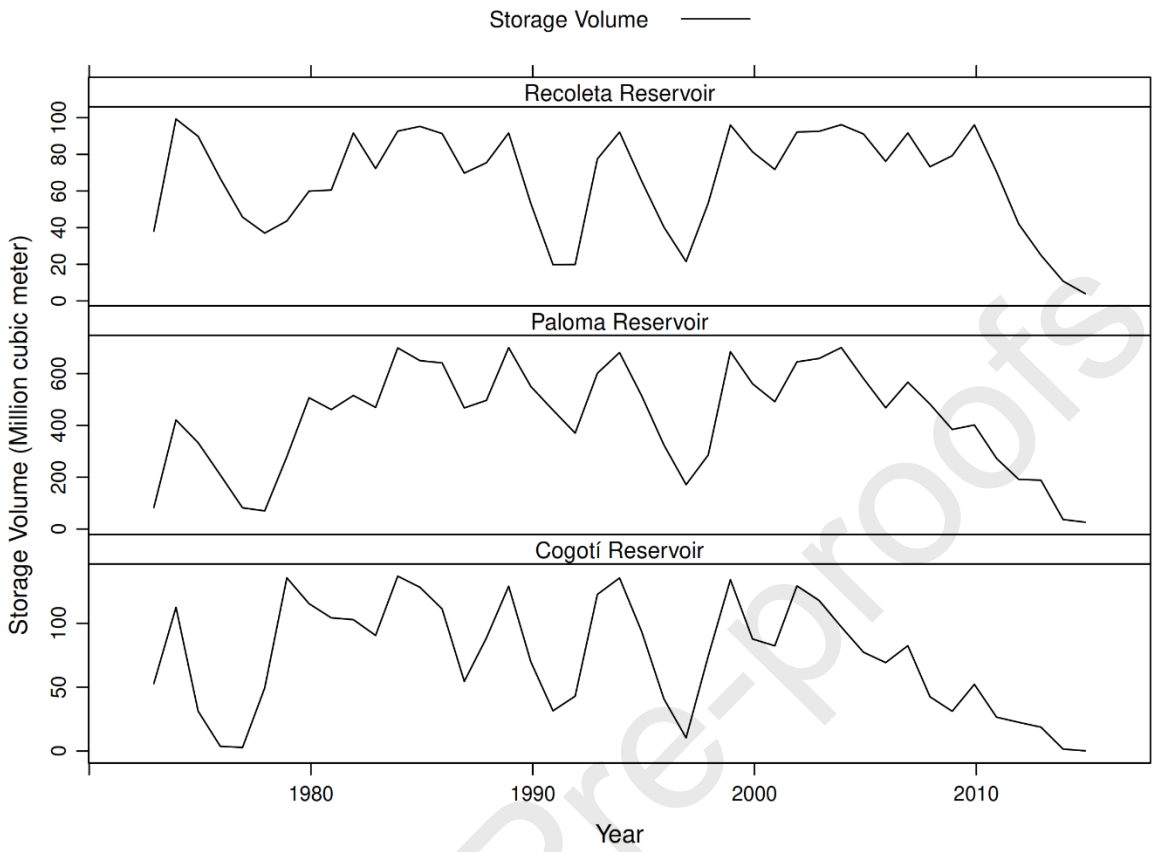

Figure 6 Storage volume (Mm^3) for the Recoleta, Paloma and Cogotí reservoirs since 1971

3.1.2. Define sector-specific objectives and key performance indicators

In conversation with the local stakeholders, a set of 'performance metrics' were identified, that represent vulnerable components of the hydrological system in the river basin with respect to the overall water security. The following performance metrics were selected to evaluate drought impact on the water security of the Limarí river basin: i) Water level of the large multipurpose reservoir 'La Paloma'; ii) Unmet demand of irrigation of fruit trees in the 'Grande' subsection of the river basin; and iii) Supplied demand of drinking water in the main city of Ovalle.

In conversation with the local stakeholders, the climate stress test was concentrated on the main multipurpose reservoir where the largest part of the water allocation in the river basin depends upon. To evaluate the water security of the river basin, a set of regulations and priority allocations need to be taken into account, to ensure correct modeling of water allocations under climate change scenarios. These regulatory constraints were identified and

consist of: i) the dead storage of the Paloma reservoir that does not allow further extraction; and ii) preferential allocation of drinking water over other water usage (irrigation, hydropower, mining).

The principal water security challenge is to manage the water allocation taking into account seasonal and interannual variability. The appropriate scale for the climate stress test is therefore a monthly time step.

3.1.3. Define critical water security limits for the indicators identified

For the chosen performance metric, a critical threshold needs to be defined. When analyzing the storage volume of the Paloma Reservoir in Figure 6b, significant fluctuations have been observed over the last thirty years, reaching very low storage volumes close to 0% during the mega drought (2010-2015). Associated impacts of these very low levels have been identified, which allows defining a reservoir level with proven negative impact on (agricultural) productivity. Therefore, the 10th percentile was first proposed as a threshold to identify water insecurity in the river basin, which gives a value of 330 Mm^3. In conversation with local stakeholders, this value was confirmed to be a relevant critical value, as it constitutes three times a reserve of 110 Mm^3, which is the close to the minimum required allocation amount to ensure irrigation of the currently cultivated and irrigated lands, allowing to secure the current crops for a period of three years even under extreme drought conditions.

3.2. Step 2 - Vulnerability Analysis

Climate Stress Test

Several stations containing historical precipitation (36) and temperature (12) data for the province of Limarí were accessed through the www.climatedatalibrary.cl, a centralized portal in support of climate risk management. A selection of 14 stations was made after thorough screening of the available data, in which stations containing several years of missing data were excluded. A common period of available data was selected from January 1969 until December 2014.

As part of the preprocessing procedure (Figure 3), the gaps in some of the daily precipitation and temperature records were first removed and the dataset detrended using the multimodel ensemble climate change trend. This was followed by a wavelet analysis that indicated that

no deterministic processes were present in the observed dataset, confirming that the annual variability can be best explained by random processes presented by the VAR model. Since only the first order was found significant, a first order autoregressive model or AR(1) was used. The intervariable correlations between the precipitation and temperature data were compared, and showed very similar results for the observed and simulated timeseries, indicating that the simulated timeseries are consistent with the observational record. In Figure 7 the annual and decadal synthetic timeseries is presented for the Limari river basin, showing clearly the annual and decadal variability present in the timeseries, consistent with the observed data series.

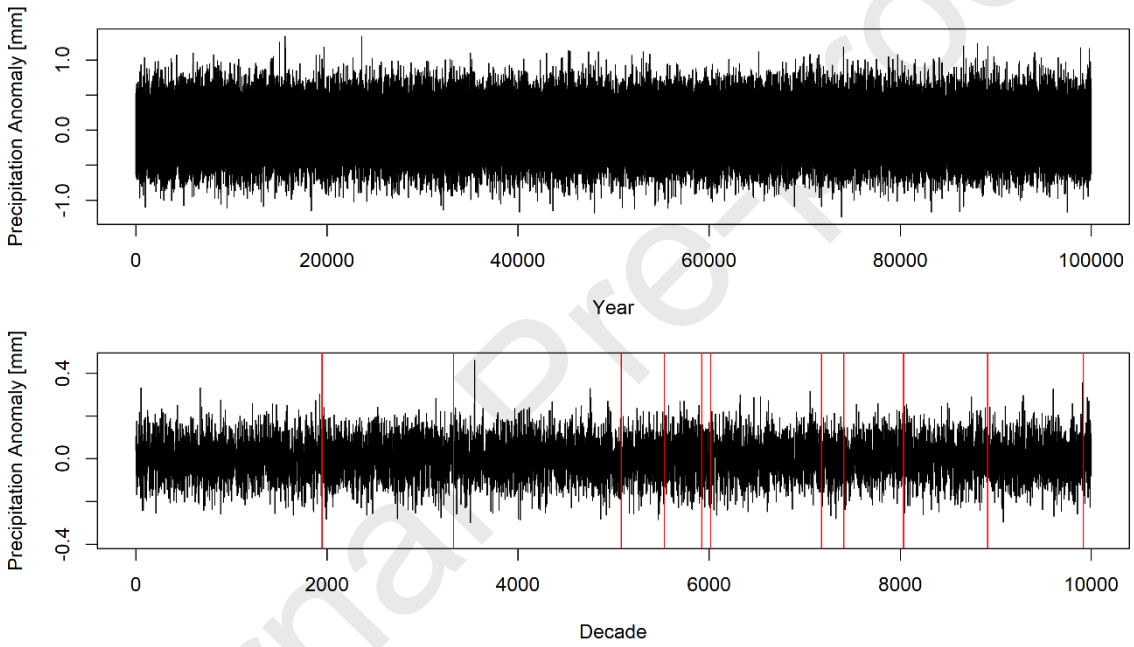

Figure 7 Synthetic timeseries of 100K years of precipitation, showing the natural variability in the Limari river basin a) annually and b) for every decad. The red lines indicate decades with drier than normal conditions (10th percentile).

In the next step of the process (Figure 3), the observations of the Limarí river basin are compared with the historical IPCC CMIP5 model results, to identify models capable of reflecting the current conditions of precipitation and temperature. This was performed by selecting the average of the GCM cells that overlay the Limari basin, or a single cell in the case of GCMs that operate at a lower resolution and encompass the basin in a single cell.

A list of correlations between observed and modeled precipitation values provides a first estimate of this model accuracy (Table 1). A threshold of $R^2 = 0.15$ is used to detect those GCMs that perform weakly in representing observed conditions. These GCMs are subsequently removed and are not used for further modeling, reducing the number of GCMs used in the analysis to 34 out of 44 (Table 1).

Table 1 Correlations between the monthly precipitation values of the GCMs and the observed data for the period 1981-2010.

Correlation Coefficient (R^2)			
0.03 - 0.15	**0.15 - 0.25**	**0.25 - 0.35**	**0.35 - 0.42**
GISS-E2-H	GISS-E2-R-CC	CMCC-CMS	FGOALS-g2
NorESM1-M	HadGEM2-CC	IPSL-CM5A-LR	bcc-csm1-1
NorESM1-ME	GFDL-CM3	CMCC-CM	CMCC-CESM
inmcm4	ACCESS1-3	HadGEM2-ES	MRI-CGCM3
CNRM-CM5	CSIRO-Mk3-6-0	MIROC5	FGOALS-s2
MRI-ESM1	CanESM2	MIROC-ESM	
GISS-E2-H-CC	CCSM4	GFDL-ESM2G	
IPSL-CM5A-MR	CESM1-WACCM	CESM1-CAM5	
CESM1-BGC	MPI-ESM-LR	IPSL-CM5B-LR	
	bcc-csm1-1-m	ACCESS1-0	
	CESM1-CAM5-1-FV2	GFDL-ESM2M	
	EC-EARTH	GISS-E2-R	
	MPI-ESM-MR	BNU-ESM	
	MIROC-ESM-CHEM	HadGEM2-AO	
		FIO-ESM	

In the next step, a distribution is generated that displays the expected change in annual precipitation (percentage increase or decrease) for each degree of warming for the Limarí Basin (Figure 8). It shows that 24 out of the 34 selected GCMs project a decrease of precipitation for each degree of global warming, with an average decrease of 4%. This suggests a rather strong drying in the Limarí basin associated to the projected temperature increase due to global warming.

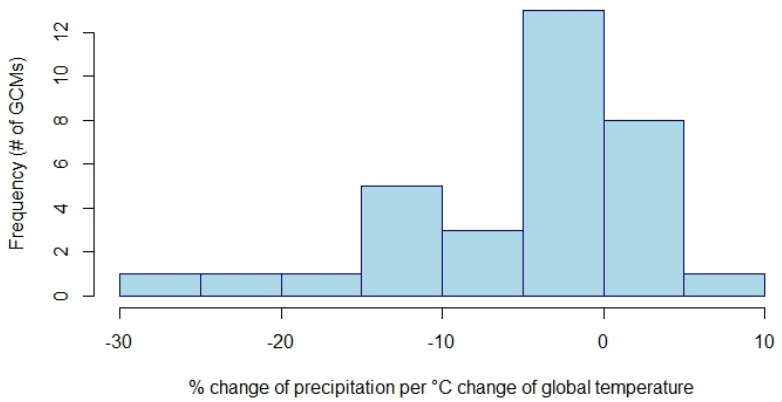

Figure 8 Histogram of the 34 GCMs selected for the Limari Basin, expressing the percent change in local annual precipitation per degree of global warming

In the final step, the SIMGEN weather generator is used to generate probabilistic timeseries, allowing to explore the full spectrum of uncertainty. As an example, in Figure 9 a set of different future projections for precipitation and temperature is given for different runs using the 50th percentile of the GCM distribution (Figure 8) for the Limari basin. The scatter observed originates from natural annual and decadal variability that is present in the synthetic data series (Figure 7). In combination with the spread in the GCM distribution, a large variability can be sampled, thereby providing a pathway to represent uncertainty in the model projections.

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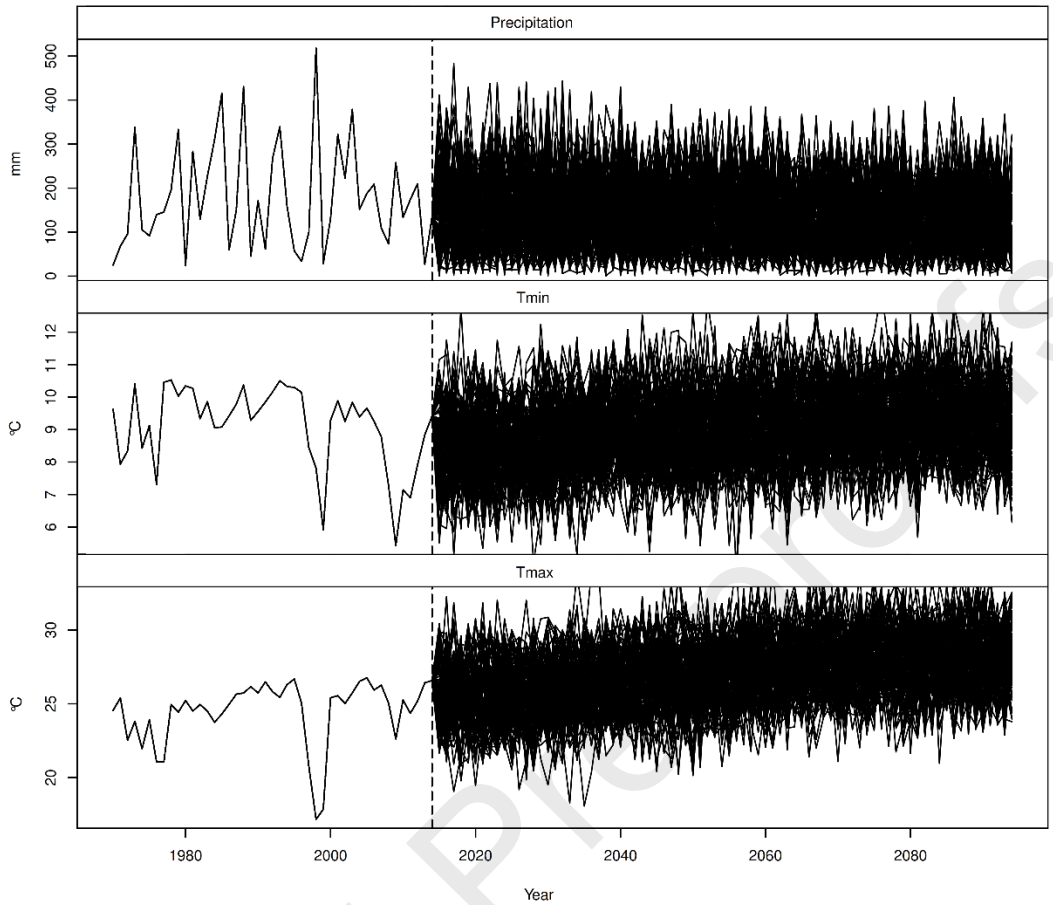

Figure 9 Projected timeseries for the Limari Basin showing annual precipitation, minimum temperature (Tmin) and maximum temperature (Tmax) for the 50th percentile

In the final step of the climate stress test, the climate projections are applied to the hydrological model. The hydrological model used for the stress test in the Limari Basin is the Water and Evaluation and Planning (WEAP) model (Johnson et al., 1995). The WEAP model for the watershed contains 19 river sections, 3 reservoirs and 120 subcatchments (Figure 10), and is described in detail in Vicuña et al. (2012).

As the Limari basin is a snow-driven system, particular attention was given to ensure the precipitation in high altitudes would be stored as snow in winter time and released as discharge when temperatures increase (Figure 2). Therefore, the upper basin is divided in bands of similar altitude with similar climatic conditions that are corrected using temperature-altitude gradients and precipitation-altitude relations. Snow is generated when preciptation is received below the freezing point and runoff is generated when temperatures

rise above the melting point, thereby adequately representing the snow-melting feature in spring time which is characteristic for the basin. The population increase has also been incorporated in the model as a yearly increase of 2% in line with the population increase over the 2002-2015 period.

A disadvantage of the WEAP model is the limited functionality to simulate groundwater flow, as WEAP uses a simplified approach, where groundwater needs to be assigned to a river node. As a result, groundwater is modeled with limited detail, although the model has shown to adequately represent the observed aquifer variations during the monitoring period, as well as the aquifer-streamflow interactions (Vicuña et al., 2012).

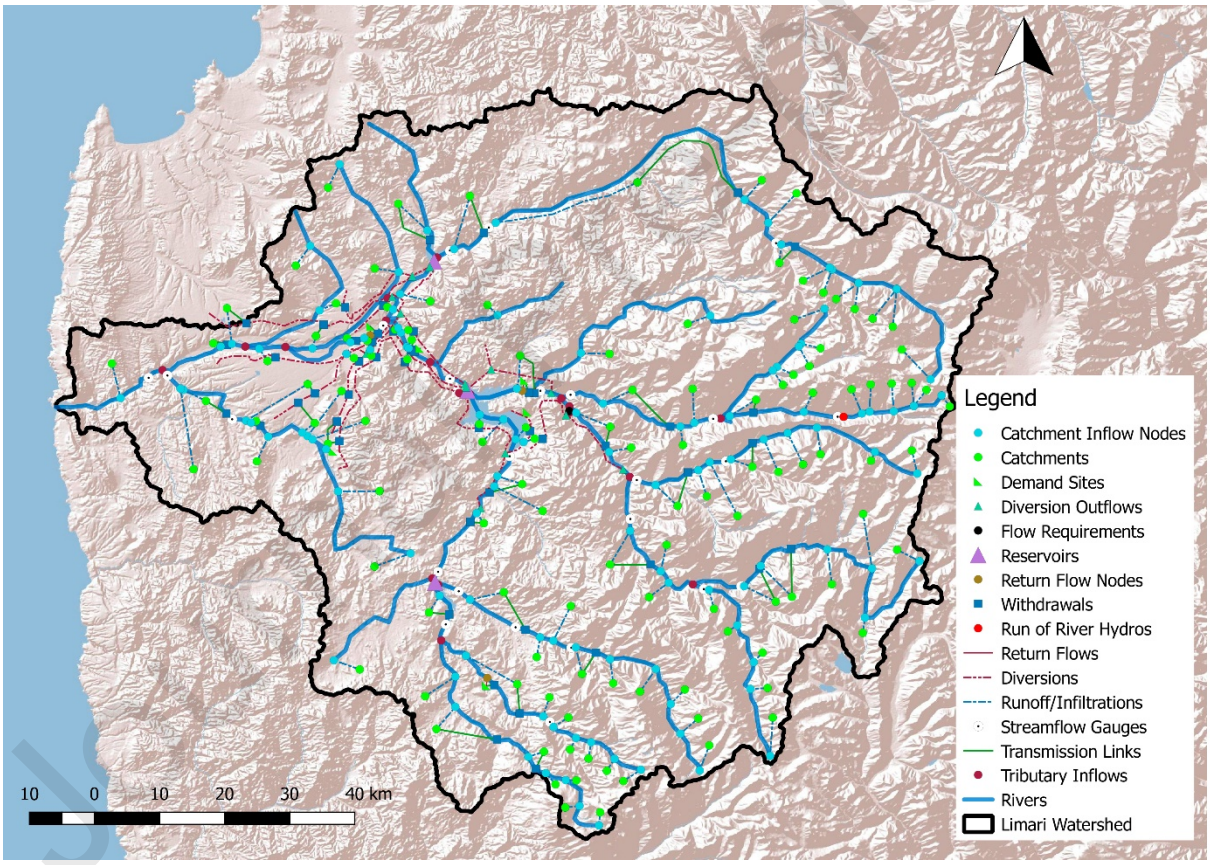

Figure 10 Visual representation of the hydrological WEAP model for the Limari water basin

Using the WEAP model as a diagnostic sensitivity tool, the response of the system is identified with respect to changes in temperature and precipitation. In Figure 11 the response surface is presented for the level of the La Paloma reservoir, showing the reservoir volume

for different combinations of temperature and precipitation. The response surface was generated by sequentially adjusting the monthly historical data used in the calibration of the model, by incrementing or decreasing the observed precipitation and temperature values by 10% at a time. The corresponding response of the hydrological model in terms of reservoir level was then averaged. To explore the full spectrum of possible values, a broad range of observed and potential values was used, evaluating an average annual temperature range of 8 °C until 24 °C, and an annual precipitation amount ranging from 100 mm until 190 mm.

This shows that the reservoir level is more sensitive to precipitation changes than to temperature changes. When the annual precipitation drops from 180 mm to 120 mm, the reservoir level drops from around 600 Mm^3 to a level more closely to 200 Mm^3, which is below the critical threshold level of 330 Mm^3 identified by the stakeholders. The temperature influence on the reservoir levels is more limited, but reservoir volumes are reduced when moving from a low temperature (e.g. 10°C) to a high temperature (e.g. 24°C), as a result of an increased evaporation. When moving to average annual temperatures below 10°C, a more significant amount of precipitation is stored as snow and ice in the watershed, as the temperature in the higher altitudes of watershed drops below zero, causing a reduction in the available reservoir volume.

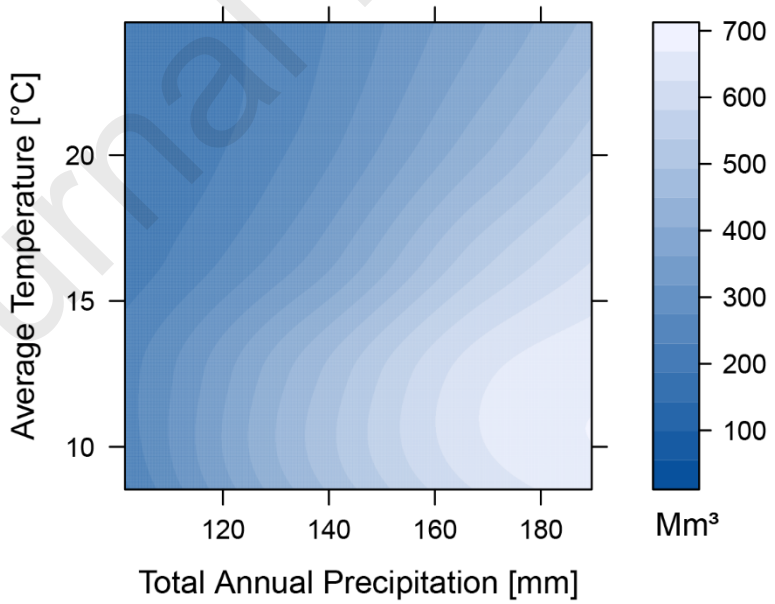

Figure 11 Response surface of the La Paloma reservoir volume (Mm^3) for different temperatures and precipitation values

To evaluate how climate change is affecting the reservoir inflow, information on observed and projected climate conditions needs to be integrated into the response surface. Using the historical record, the average historical reservoir level is characterized for the basin using the observed data. Additionally, several projected timeseries are plotted on the same graph, which allows to identify the impact of climate change on the reservoir level, and what the range of possible future climates sampled from all the different climate models means for the local reservoir level.

Figure 12 shows the changes in expected precipitation and temperature in relation with the reservoir levels of the La Paloma reservoir, compared to the average historical values. This shows a projected shift from an average temperature of 16.9°C and an average annual precipitation amount of 168 mm in the period 1981-2010 towards higher temperatures and lower precipitation values in the following decades. Following the sensitivity analysis presented in Figure 11, it is clear from Figure 12 that these projected values violate the critical value established for the volume of the La Paloma Reservoir (330 Mm^3). Although there is significant variability between decades, showing wetter and drier conditions, in these projections there is evidence that the climate change projections will have a negative impact on the water reservoir level of the main reservoir in the watershed.

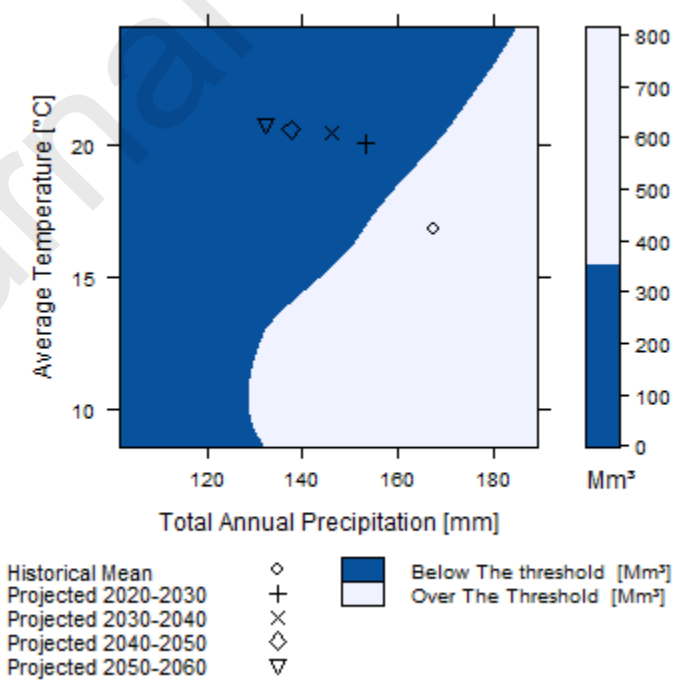

Figure 12 Response surface for the La Paloma reservoir level (Mm^3) for different temperature and precipitation levels, with indication of the historical observations and average projected climatic conditions for the next five decades using the 50th percentile of the RCP 8.5 projections, as well as the critical threshold of 330 Mm^3

In Figure 13 an example timeseries is presented for the 50th percentile of the RCP 8.5 projections, showing several episodes where the reservoir volumes are below the critical threshold for several years, especially towards the end of the century. This confirms that the projected reductions in precipitation are expected to progressively affect the water security in the Limarí basin.

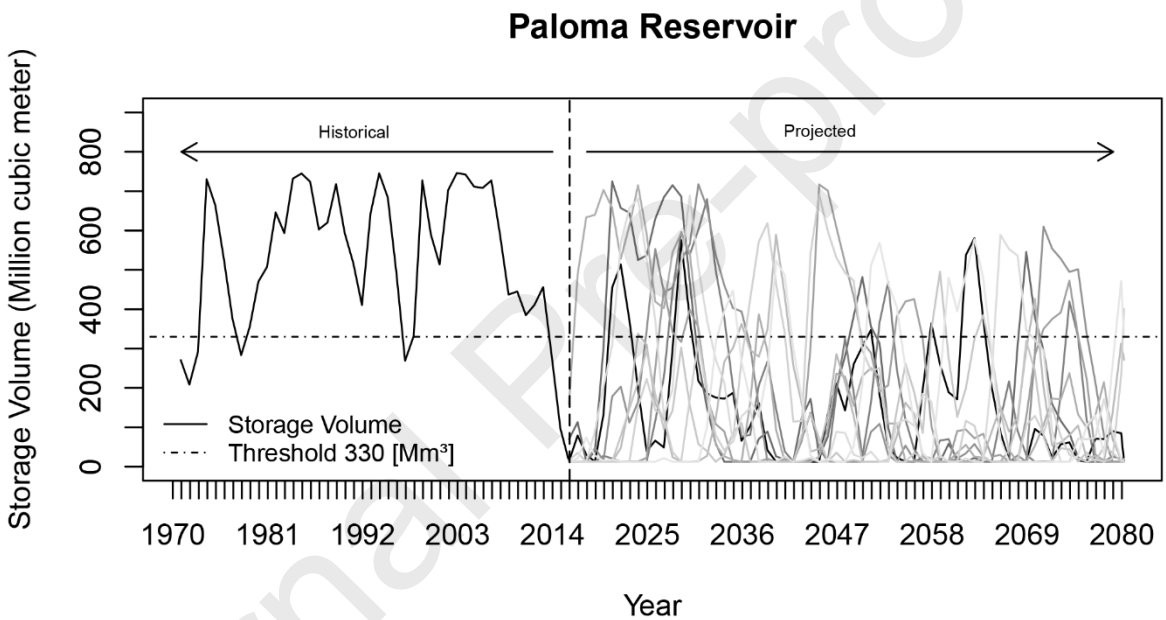

Figure 13 Water volume of Paloma Reservoir (million cubic meters) for a median future scenario (Percentile 50) of the RCP 8.5 projections

The Level of Concern Analysis

The final step of the vulnerability analysis consists of a Level of Concern (LOC) analysis. This involves the evaluation of two different criteria for the Limarí river basin.

The first component of the LOC, focusses on the risk of climate change, which is a function of i) the level of impact of surpassing a critical performance threshold and ii) the plausibility of these future impacts. To evaluate the plausibility of climate change impact, a transect is created in the response surface between the historical and projected values of temperature

and precipitation, to assess the sensitivity of the system and is also often termed 'elasticity'. This elasticity can be expressed with respect to any of the two climate drivers, precipitation or temperature, as presented in Figure 14. This elasticity allows identifying how fast the reservoir volume changes with respect to changes in temperature or precipitation.

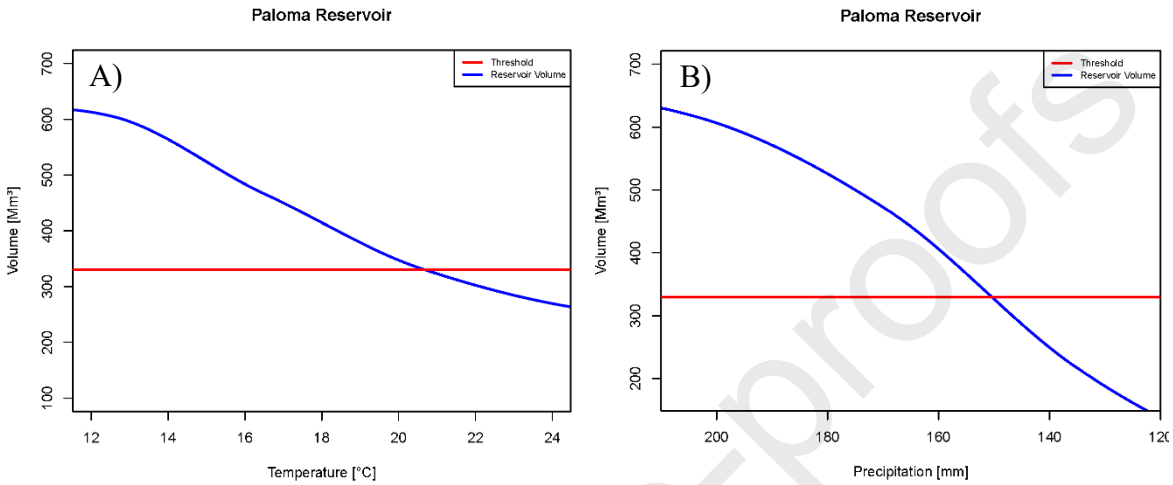

Figure 14 Elasticity of the La Paloma Reservoir with respect to the climate drivers a) temperature and b) precipitation for the 50th percentile of the RCP 8.5 projections

In both graphs a clear decay in the reservoir volume is observed with increasing temperatures and decreasing precipitation. Based on this analysis, it is clear that the reservoir volume is highly sensitive to changes under plausible futures, indicating a significant risk of negative climate change impacts and a lower water security. This suggests that the minimal acceptable reservoir level is likely to be reached more frequently under climate change projections.

As indicated by Figure 4, the assessment of plausibility also requires an evaluation of the spread in the climate change projections. To quantify this spread of GCM responses, the distribution is sampled to evaluate the consistency of the signal among the 34 selected GCMs, providing an assessment of the uncertainties in the projections. Therefore, transects are created between the average historical conditions and the projected temperature and precipitation for a dry scenario (10th percentile), a median scenario (50th percentile) and a wet scenario (95th percentile). These transects in Figure 15 show how the different scenarios present a different elasticity, or different change in reservoir volume with decreasing precipitation.

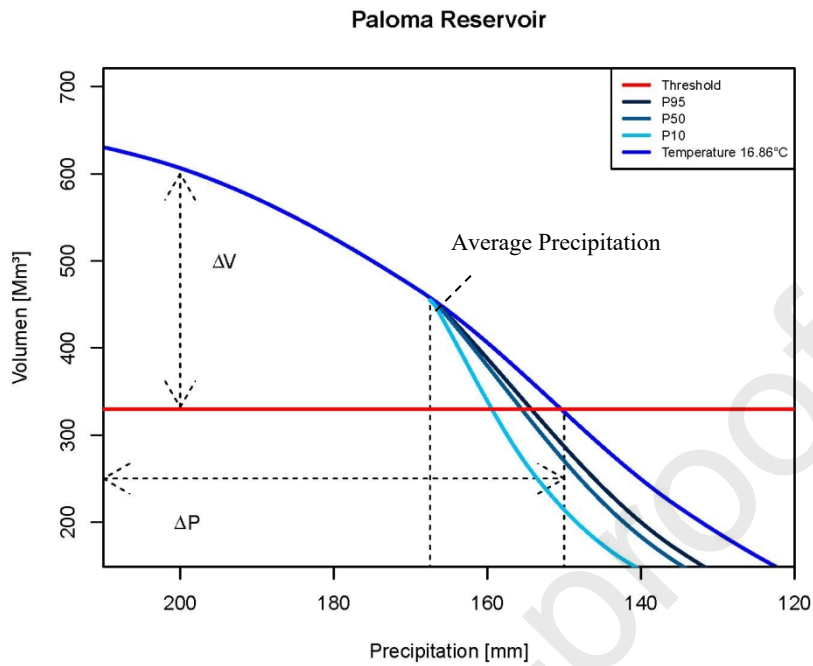

Figure 15 Sensitivity of the reservoir volume for different model simulations (10th, 50th and 95th percentile) of the RCP 8.5 projections for the 2030-2060 decade, to assess plausibility of surpassing a critical threshold, compared to the historical observation range for an average temperature of 16.9°C

For all future scenarios, the critical threshold is expected to become overpassed more rapidly in a warming scenario compared to current conditions. The driest scenario (10th percentile-P10) indicates a fast reduction of reservoir volume with decreasing precipitation and increasing temperatures, as this scenario represents the GCMs that project much drier conditions for each degree of warming. The median scenario (50th percentile) also presents an adverse condition, but the elasticity is lower, as such projecting a lower reduction in water storage for each degree of warming. The wet scenario (95th percentile) represents the GCM models that show an increased precipitation for each degree of warming, resulting in a lower loss of reservoir storage volume for each degree of warming. Nevertheless, even for this wetter scenario, the critical threshold is overpassed in the horizon 2030-2060 due to higher temperature effects. This introduces the second component of the LOC analysis that focusses on the uncertainty associated with the climate stress test, which originates from three different sources.

A first source of uncertainty comes from the data used to define the critical threshold. As the reservoir level is measured daily and converted to a monthly average level, the analytical uncertainty is considered low. The system model provides the second source of uncertainty. The hydrological model has a moderate to high Nash-Sutcliffe Efficiency (NSE) between 0.7 and 0.9 for the different river reaches (Vicuña et al., 2012), suggesting a medium to low uncertainty of this component. The third component originates from the future projections that contain large uncertainties, due to the uncertain future scenarios used in the GCM projections. Figure 15 can also be used to assess the uncertainty on the different projections, indicating a moderate spread on the GCM scenarios for the case study, resulting in medium to high analytical uncertainty.

Combining the different criteria, a level of concern analysis indicates what the level of urgency should be to address the threat of climate change impact on the water resources allocation in the watershed.

Using a Climate Risk Matrix such as the one presented in Mendoza et al. (2018), a risk assessment for the Limarí basin can be made, by evaluating impact and plausibility. For the impact assessment a critical threshold has been defined at 330 Mm^3 as a lower limit beyond which significant risk for water insecurity occurs. When evaluating the median scenario (50th percentile), the temporal analysis of the reservoir volume (Figure 13), combined with the sensitivity analysis (Figure 11), has shown that there is a high risk for the La Paloma Reservoir to enter a period of lower reservoir volumes due to climate change impact. The second aspect of the risk assessment concerns the plausibility of this scenario to occur. Therefore, the full distribution of plausible GCM projections are sampled (from the distribution presented in Figure 8) to evaluate the consistency of the model projections with respect to the reduction in reservoir volumes. From Figure 15 it is clear that the full range of GCMs project a negative impact on the volume of the La Paloma reservoir. Using the guidelines presented in Mendoza et al. (2018), a high plausibility was assigned to the violation of the critical level of the reservoir by 2050. As a consequence, a high risk was assigned to breach the critical threshold for the La Paloma reservoir level of the Limarí, as there is a high plausibility for entering a future state with a negative impact for the water security of the watershed.

By combining the risk assessment (high) with the analytical uncertainty (medium to high), the level of concern analysis leads to a recommendation for the implementation of robust and flexible solutions (Figure 5), that can be used to further develop the third step of the CRIDA approach on the identification of adaptation pathways.

4. Conclusions

This paper presents a novel climate stress that allows assessing the impact of climatic and non-climatic drivers on the water security of river water basins. The methodology presented, supports the first two steps of the recently launched Climate Risk Informed Decision Analysis or CRIDA (Mendoza et al., 2018). Through a pilot case study, a climate stress test was demonstrated for a vulnerable mountain catchment in Chile, to identify water security hazards under climate change projections. By engaging local stakeholders early in the process through a collaborative, bottom-up approach, the performance indicators and the critical thresholds were identified beyond which significant economic impacts occur.

The second part of the climate stress test identified the expected climate projections under a warming scenario (RCP 8.5), as projected by a set of 43 Global Circulation Models (GCMs), of which 34 were retained in the final analysis as they best represented the observed past conditions. The full distribution of projected precipitation and temperature changes under a warming climate was explored for the pilot basin, showing an average reduction of 4% precipitation for each degree of warming.

By sampling from the wide range of GCM trends, the climatic projections were ingested by the hydrological model for the basin to identify the sensitivity of the basin to climate change impacts, as well as to assess their plausibility. For all evaluated projections, the violation of the critical threshold is plausible, due to a combination of higher temperatures and reduced precipitation for most scenarios. A high level of concern is assigned to the climate stress for the Limarí river basin, suggesting that adaptation strategies should be developed to address the increased climate risk and the expected water insecurity due to insufficient reservoir volumes during extended periods. Given the uncertainty associated to the analysis, a combination of robust and flexible adaptation measures is recommended for the Limari basin.

A gap was identified that no clear impact assessment has been realized after the last multiannual drought (2010-2015), which makes it difficult to quantify the economic impact

of long-term droughts, which is important to identify critical thresholds for future drought events. The previous mega-drought already required farmers to adjust to these new conditions, driving the development of adaptation strategies at the farmer level, such a as the application of deficit irrigation, experiments with drought-resistent crops, etc. Based on these experiences, the current climate stress test framework will be further expanded in follow-up research to evaluate adaptation pathways for the basin, by assessing how the combined effect of different adaptation strategies can effectively offset the negative impacts of climate change.

In future work, the level-of-concern analysis would also benefit from a quantitative approach to assess the plausibility and impact of climate change, as well as to provide more quantifiable indicators of analytical uncertainty, as these components are crucial to identify the urgency for adaptation strategies to be implemented, as well as the type of adaptation actions that are most suitable to address the threat.

Apart from climatic drivers, there are other stressors that might affect negatively the water security of the water basin. Although the framework presented can simultaneously address multiple drivers, assessing the uncertainties associated with these additional drivers, such as crop prices, remains a challenge that needs to be addressed.

The climate stress test presented in this paper provides a framework to assess the water security of a local watershed under climate change scenarios. The bottom-up approach, starting with a stakeholder consultation, provides a pathway to anchor climate change information in a local context that is relevant for decision making, moving away from the more generic downscaling techniques that provide a physical vulnerability assessment, but fail to address the impacts on the ground. Therefore, it is expected that the climate stress test presented in this paper, will be a valuable tool in other water security contexts, given its general applicability and universal setup.

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